Artificial Intelligence in Knowledge-Intensive Task Automation: Insights from the Social Learning Cycle

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Abstract: These days, we are witnessing with amazement the exponential increase in the possibilities of AI in tasks that only a few months ago we thought were reserved for humans. This work aims to study how AI is impacting the way we perform knowledge-intensive tasks by addressing the following research questions: How does AI impact the learning process? Are new kinds of learning cycles fueled by AI? Or even, is AI capable of using and creating knowledge without learning? To explore this, we rely on Boisot's I-Space theoretical knowledge management framework, which proposes a model of how learning happens within a three-dimensional space via the so-called Social Learning Cycles (SLC). The SLC explains how information flows in a social system and, consequently, how knowledge is generated, transmitted, and applied. Our work examines the evolution of automation as a basis for scalability, now applied to knowledge tasks. Specifically, we analyze how AI impacts the SLC. Scalability was the foundation of the Industrial Revolution, as it enabled the mass production of goods and the emergence of economies of scale. It began with craftwork, assisted production, the systematization of tasks, and their automation. Now, for the first time in human history, AI allows the automation of complex knowledge tasks, even creative ones such as image generation. Moreover, other types of tasks based on analysis, review of information, and decision-making can be completely automated, leveraging the massive power of AI processes (i.e., vast datasets and computational capacity). As a second objective, our work studies how the evolution of knowledge-intensive automation is driving greater scalability. Drawing on a multiple-case study of organizations implementing AI in knowledge-intensive activities, the paper presents two main contributions. First, the findings suggest that the adoption of AI may decouple the learning process from human agency, proposing that the fifth stage of the SLC model, Absorption, may undergo a significant reconfiguration. This suggests that organizational learning built on shared individual experiences could be fundamentally altered. Second, the authors introduce a curve that synthesizes the exponential relationship between cognitive automation and efficiency gains, demonstrating a new form of scalability analogous in its potential impact to the manufacturing transformations of the Industrial Revolution.

Keywords: Artifical intelligence, Social learning cycle, Organizational learning, Automation, Knowledge-intensive, Scalability

1. Introduction

These days, we are witnessing with amazement the exponential increase in the possibilities of AI in tasks that only a few months ago we thought were reserved for humans.

This work aims to study how AI is impacting the way we perform knowledge-intensive tasks by addressing the following research questions: How does AI impact the learning process? Are new kinds of learning cycles fueled by AI? Or even, is AI capable of using and creating knowledge without learning? To explore this, we rely on Boisot's I-Space theoretical knowledge management framework, which proposes a model of how learning happens within a three-dimensional space via the so-called Social Learning Cycles (SLC). The SLC explains how information flows in a social system and, consequently, how knowledge is generated, transmitted, and applied. Our work examines the evolution of automation as a basis for scalability, now applied to knowledge tasks. Specifically, we analyze how AI impacts the SLC.

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The qualitative empirical work is based on the study of real cases through the perception of their protagonists, who are implementing AI in knowledge-intensive activities.

2. Theoretical Context

In any domain, new activities begin as manual, exploratory processes that rely heavily on individual expertise. To achieve scalability, organizations systematize these activities by clarifying steps and documenting procedures, an initial investment that builds efficiency (Parasuraman et al., 2000). Once structured, tools such as checklists and decision-support systems are introduced to assist human performers, transitioning to human-in-the-loop guidance (Miller & Parasuraman, 2007). The final stage is automation, in which tasks are fully or partially delegated to software and machines, executing explicit processes with minimal human intervention (Bernabei & Costantino, 2024). This evolution informs the understanding of automation maturity.

2.1 General Process Automation

Business Process Maturity Model (BPMM)

Understanding the evolution of business processes through progressive levels of maturity is essential to studying the foundations of automation in productive activities. The Business Process Maturity Model (BPMM) provides a structured framework for assessing the capability of an organization's processes to deliver predictable, efficient, and continuously improving outcomes. BPMM builds on earlier maturity models such as the Capability Maturity Model (CMM) developed by the Software Engineering Institute (Lee et al., 2007). The model is composed of five maturity levels (Weber et al., 2008): initial, managed, standardized, predictable, optimizing.

A Maturity Model for the Autonomy of Manufacturing Systems.

This model, introduced by Fan Mo (Mo et al., 2023), is especially relevant in manufacturing and industrial automation. It emphasizes the progression from tool-based support to fully self-regulating systems. The model includes five levels: no autonomy, assistance, partial autonomy, conditional autonomy and full autonomy

Business Process Reengineering (BPR)

Hammer and Champy introduced BPR as the radical redesign of business processes to achieve dramatic performance improvements (Hammer & Champy, 1993). While BPMM and CMMI advocate for gradual maturity, BPR promotes disruptive reconfiguration, providing an important alternative logic for initiating automation.

2.2 Robotic Process Automation

Robotic Process Automation (RPA) is an emerging form of business process automation technology based on software robots that mimic human interactions with digital systems. It is particularly relevant in domains where routine, rule-based tasks dominate, such as administrative, financial, and back-office operations (Lacity & Willcocks, 2016). RPA is grounded in several theoretical streams:

- Task-Technology Fit Theory (Goodhue & Thompson, 1995)
- Socio-technical Systems Theory
- Capability Maturity Models

Additionally, RPA is often linked to business process reengineering (BPR (Chakraborti et al., 2020).

2.3 Knowledge and Intelligent Process Automation (IPA)

A more technological approach was published in 2019 by the IEEE Standards Association: the Software Based Intelligent Process Automation (SBIPA), IEEE 2755.1 (Hood, 2019). It has become very popular in the 'industry 4.0' literature.

RPA relies on explicit algorithms, requiring encoded functionality, that cannot evolve or adapt to new situations or events. It is therefore most effective for automating very repetitive tasks.

Another variant is Cognitive Process Automation (CPA), which uses probabilities to drive automation decisions. In this case, AI can adapt and learn from new data.

The Process for Knowledge Automation: APeM

This model, developed by Yotung Wang (Wang et al., 2023) integrates autonomous modes (AM), parallel modes (PM), and expert/emergency modes (EM), collectively referred to as APeM. It automates workflows on knowledge factories, accounting for over 80% of operations in the autonomous mode.

2.4 Knowledge-Intensive Processes and AI

Knowledge Creation and Transformation (SECI Model)

The SECI model developed by Nonaka and Takeuchi (1995) offers a dynamic theory of knowledge creation through four modes: Socialization, Externalization, Combination, and Internalization. These phases capture the transformation of tacit knowledge into explicit, shareable forms, which is essential for systematizing tasks and eventually embedding them in technological systems. The model's emphasis on abstraction and codification provides a bridge between human-centered craft and machine-executable procedures, essential in automation design.

I-Space and the Social Learning Cycle

Boisot's I-Space framework conceptualizes the flow of knowledge through three dimensions: codification, abstraction, and diffusion (Boisot, 2013). The Social Learning Cycle (SLC) within the I-Space model describes six phases:

- Scanning: Identifying weak signals from unstructured data.
- Codification: Structuring and clarifying insights.
- Abstraction: Generalizing insights into broader principles.
- Diffusion: Disseminating structured knowledge.
- Absorption: Applying knowledge through practice.
- Impacting: Embedding knowledge into systems and routines.

The I-Space highlights the tension between the utility of knowledge (through codification and abstraction) and its scarcity (through limited diffusion). It provides a theoretical foundation for understanding how knowledge becomes machine-processable and thus automatable.

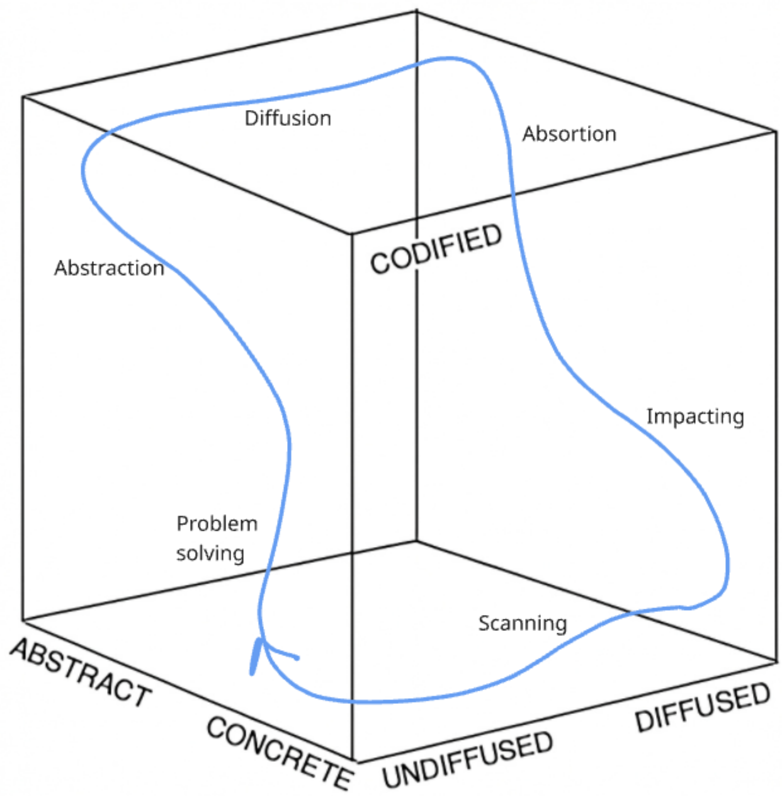

Figure 1: The Social Learning Cycle. Source: Boisot, 1998

Stages of Automation in Digital Work

The model conceptualizes automation as a continuum, particularly within knowledge work, rather than a binary state. It frames automation not as replacement, but as augmentation and transformation of knowledge work. The relevant stages of automation are: assisted, augmented and autonomous intelligences (Davenport, 2018).

3. Research Questions

The rise of AI, particularly large language models, machine learning systems, and expert systems, is reshaping how cognitive work progresses through the I-Space. These shifts suggest that AI accelerates movement through the Social Learning Cycle but may also bypass key human phases such as absorption or institutional validation

Our research questions are:

- AI enables transition from craft to automation in cognitive work
- Adopting AI in cognitive processes modifies some steps of the I-Space SLC.
- AI reduces the need for human-led abstraction by externalizing pattern recognition to statistical systems.
- AI automated knowledge tasks make knowledge less likely to be culturally embedded than socially-produced knowledge.

4. Research Design and Methodology

The qualitative research adopts a multiple-case study design (Yin, 2018) to explore how AI is enhancing and automating cognitive tasks in knowledge-intensive environments. This approach allows for an in-depth, contextualized investigation of complex socio-technical processes that cannot be easily isolated or quantified. Multiple cases enable analytical generalization by comparing patterns across settings rather than aiming for statistical representativeness.

The study includes purposefully selected cases that represent diverse organizational contexts, sizes, and industries. The analyzed activities in several companies are knowledge-intensive, and they differ in the type of knowledge involved (visual, strategic, engineering), offering variation in cognitive task structure and the role of AI technologies.

Table 1: List of cases analyzed in the research. Source: Authors' elaboration

Case	Industry	Organization
A	Health	A public sector institution that promotes and develops biomedical research
B	Manufacturing	A graphic design and manufacturing company
C	Marketing services	A digital marketing agency
D	Supplies	A group specialized in water and environmental management
E	Manufacturing	A group specializing in the manufacturing of plastic piping systems
F	Science	A laboratory with the world's largest and most complex scientific instruments
G	Pharma	A pharma company

Data were collected through semi-structured interviews, internal documents, and AI-generated artifacts, ensuring triangulation and richness of insight. A guiding questionnaire was prepared covering all stages of the SLC, asking participants to compare their perceived effort before and after AI adoption.

5. Findings and Discussion

From our empirical work we have found some significant elements.

5.1 Scaling Knowledge-Intensive Activities

The evolution of automation is closely related to efficiency improvement, which we interpret as scalability in knowledge-intensive activities, much like the industrial revolution enabled scalability in goods manufacturing.

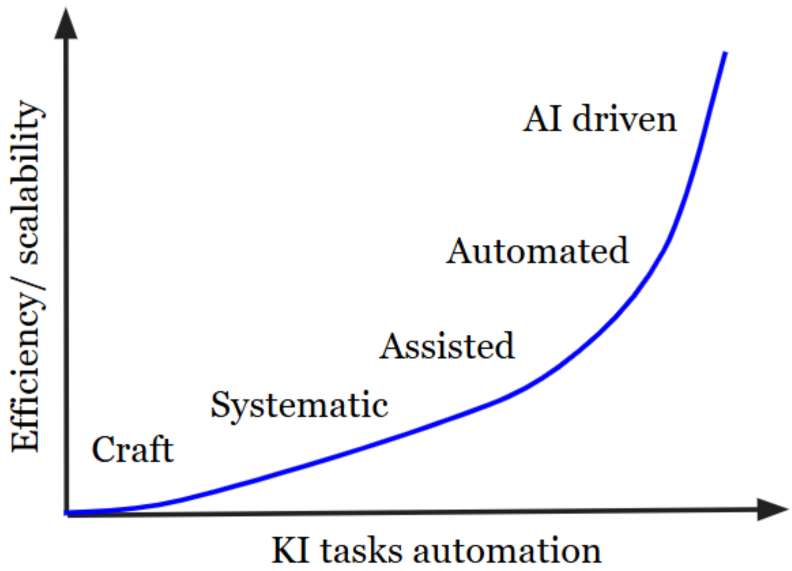

Figure 2: Automation of KI tasks and scalability. Source: own elaboration

The curve presents a clear progression through five distinct stages of automation, exhibiting an exponential rise in the "AI driven" stage. This signifies that leveraging Artificial Intelligence for KI tasks unlocks unprecedented levels of efficiency and scalability.

5.2 Impact of AI on the effort required to perform SLC steps: Basis for scalability

We analyze the perceived effort required to perform each step of the SLC compared with the initial "craft" stage, considered a strong effort.. The following table shows the effort required to perform each SLC activity.

Table 2: Required effort at each SLC step at different automation levels (very high, high, moderate, low, very low). Source: own elaboration

Stage #	Automation SLC Stage \	Craft	Systematic	Assisted	Automated	AI driven
1	Scanning	High	High	High	High	Moderate
2	Codification/ Problem solving	High	Very High	Very High	Very High	Very High
3	Abstraction	High	Very High	Very High	Very High	Low
4	Diffusion	High	Very High	High	Low	Very low
5	Absorption/ (Adoption)	High	High	Low	Low	Very low
6	Impacting	High	High	Low	Low	Very low

*It requires a high effort to contextualize, setup and train first and select provided outputs after. But its ability to manage big data and apply brute force to solve problems compensates it.

6. Conclusions and Implications

The automation curve highlights that while all forms of automation contribute to efficiency and scalability, AI-driven solutions represent the peak of this progression, offering disproportionately higher returns. They enable intelligent, autonomous operations capable of scaling rapidly and performing complex tasks with increasing effectiveness, maximizing operational capabilities in a domain that remained unscalable until now.

It should be noted that while later stages of the SLC become much less demanding, the initial stages, particularly contextualizing and training AI systems, remain effort-intensive. Nevertheless, the exponential increase in the amount of data that can be processed and the variety of tasks that can be automated clearly enhances efficiency.

The persistent "very high" effort in codification/problem solving implies that creating novel learning content or complex solutions remains a challenge. Human expertise is still needed in tasks such as providing valid and meaningful data, setting objectives, and critically reviewing outputs.

This reinforces the need for human expertise in the core design and development of social learning interventions such as:

- Previously: contextualizing, providing valid and meaningful data, providing clear objectives while keeping an open window to alternative and out of the box thinking.
- After: reviewing outputs, conducting critical evaluations, iterating, and training the AI.

"Abstraction" turns into a low-effort stage, AI's ability to reduce it from It suggests the potential of AI to assist in identifying patterns and generating generalized insights from complex data, more effectively than rule-based systems.

Required efforts for the last stages of the SLC are very low, meaning that thanks to AI, there is no need to make it very diffused at all.

The most critical implication is that adoption does not necessarily imply human learning. Stage 5 of the SLC model (Absorption) may disappear, suggesting that organizational learning built on shared individual learning could be lost.

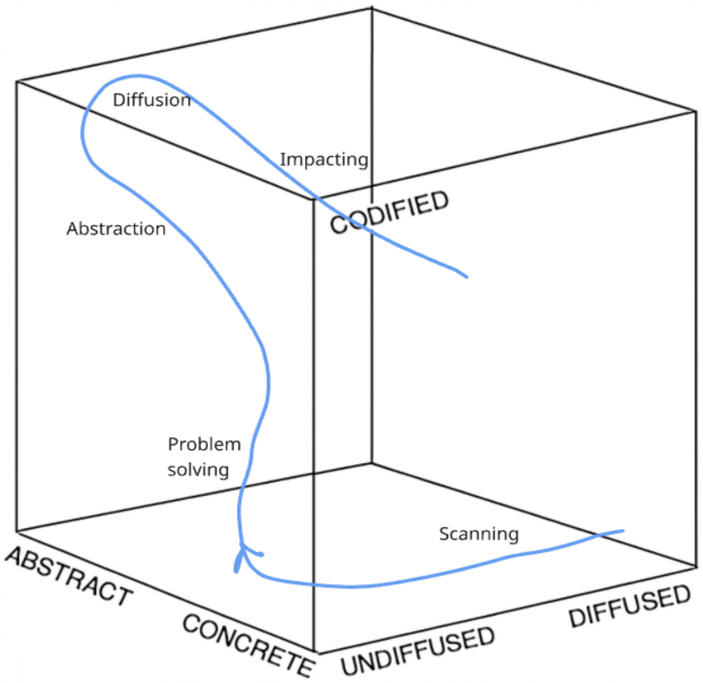

Figure 3: AI impact on the SLC. A revisited model. Source: Own elaboration

Ethics declaration: Ethical procedures for the work were meticulously followed, ensuring the protection and rights of all participants. The cornerstone of our ethical approach was the implementation of a comprehensive Informed Consent Statement. This document was presented to every potential participant to provide them with sufficient and clear information, enabling them to make a fully informed decision about their participation in the project. The informed consent process guaranteed the following ethical standards: Informed Participation: All participants were informed about the project's objective, the specific nature of their involvement, and the type of data that would be collected for analysis. Voluntary Consent: Participation in the study was explicitly stated as voluntary. Participants were clearly informed of their right to withdraw their consent and discontinue their involvement at any point without consequence. Data Protection and Confidentiality: The collection and processing of personal data strictly adhere to the General Data Protection Regulation (EU) 2016/679 and Organic Law 3/2018. Key protections included: Purpose Limitation: Personal data was collected solely for non-profit teaching and research purposes within the scope of this project. Confidentiality and Anonymization: All personal information is kept secret and will be anonymized to ensure that individuals are not identifiable in the project's results. Data Controller: The name and contact information of the Data Controller responsible for processing the data were clearly provided. Data Minimization: The data collected was limited to the minimum necessary to achieve the project's objectives, and all personal information will be permanently destroyed once the research purpose is fulfilled. Authorization for Image and Voice: Separate and explicit authorization was sought for the capture and use of participants' image and voice through audiovisual recordings, to be used exclusively for the research purposes outlined in the project. Participant Rights: Participants were made aware of their rights, including the right to access, rectify, erase, and object to the processing of their personal data. The procedure for exercising these rights was clearly explained.

AI declaration: During the preparation of this manuscript, the authors utilized artificial intelligence (AI) tools to assist with specific tasks. These tools were employed for: Text Enhancement: Reviewing and refining the manuscript for grammar, spelling, and clarity. Information Retrieval: Assisting in literature searches to identify relevant sources and background information. Source Interpretation: Summarizing and aiding in the interpretation of existing research papers. All AI-generated outputs were critically reviewed, edited, and verified by the authors. The authors take full responsibility for the intellectual content, accuracy, and final conclusions of this publication.

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